APPLICATION OF AN INTEGRATED HPC RELIABILITY PREDICTION FRAMEWORK TO HMMWV SUSPENSION SYSTEM

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ABSTRACT

This research paper addresses the ground vehicle reliability prediction process based on a new integrated reliability prediction framework. This paper is intended to provide a context for and summary of the 37 page paper published in the proceedings of at the 2010 U.S. Army GVSETS symposium, which discusses the technical details at greater length. The integrated stochastic framework combines the computational physics-based predictions with experimental testing information for assessing vehicle reliability. The integrated reliability prediction approach incorporates several computational steps to achieve reliability prediction at component and system level. The Army can use this framework to improve the reliability of the military ground vehicle fleet, including consideration of all kinds of uncertainty, especially including model uncertainty. The end result will be a tool to use in the design of a new ground vehicle for increased reliability. The paper illustrates the application of the integrated approach to evaluate the reliability of the High-Mobility Multipurpose Wheeled Vehicle (HMMWV) front-left suspension system.

1. INTRODUCTION

The Army needs to improve the reliability of its ground vehicle fleet. It is difficult to achieve reliability growth after the fleet is fielded, so the greatest improvements will come from an approach that considers reliability during the design process. This requires that methods and tools to assess the reliability of a ground vehicle be available during the vehicle design process. Reliability is essentially a stochastic measure and considers many different sources of uncertainty and variability in the vehicle and its usage to assess the probability of achieving desired performance.

A key challenge for building an adequate vehicle reliability prediction framework for military vehicles is the accurate modeling of the integration of various types of uncertainty propagation effects coming from a variety of sources in the presence of limited input and output simulation data. In addition to these uncertainty propagation effects, there are always modeling uncertainties, such as those produced by lack of data or limited number of computer simulations that should be included. The stochastic dimensionality of the vehicle reliability prediction problem increases drastically, since we start dealing with two nested spaces. In addition to the inner stochastic parameter space for the aleatory uncertainty, we will need to include an outer stochastic model space, to cover the epistemetric uncertainty.

Moreover, for building an adequate reliability prediction framework, we need to further integrate all pertinent sources of information, integrating the computational prediction results with hard evidence coming form test and field data and soft evidence coming from expert opinions. Information can come from many places, and even “soft” sources like the experience of subject matter experts should be folded into the assessment. Of course, “hard” data sources like proving ground tests and field data carry more weight, but it would be wrong to completely ignore the wisdom of seasoned experts.

We intend to produce a reliability assessment and prediction framework that will efficiently incorporate soft and hard data together (with appropriate weights) to best handle the stochastic and model uncertainties. We realize that it is unlikely that we will ever completely eliminate the model uncertainty, but we choose to handle it in a way that reduces its impact to the greatest degree possible at any time the framework is utilized, and can inform the analyst of the impact and sensitivity of the results to it.

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We have added to this a consideration of maintenance operations, to allow for incorporation of uncertainty in the maintenance inspection interval. This is a radical approach, and we believe that we are the first to do such. However, the benefits will allow for improved reliability-centered maintenance approaches to be developed using the same framework. Optimizations using this method can incorporate maintenance interval time as a design variable in the optimization process.

As a final note, this framework also includes a considerable body of work being developed separately in the area of correlated uncertainties [2]. However, while other work focuses on the correlations in uncertainty for material parameters, this framework can go beyond that to handle correlations in other ways than just material properties. More details can be found in the paper we presented at the 2010 GVSETS symposium [1]. Correlated uncertainties are becoming increasingly important for this type of work, and will likely expand in the coming years.

As an example of the framework in operation, we will consider a case study that was performed using the suspension on a High-Mobility Multipurpose Wheeled Vehicle (HMMWV). Because of publication restrictions, the model used was generic and represents an average behavior of HMMWVs without being identical to any specific variant currently in use.

The HMMWV suspension system reliability analysis consisted in the following steps:

1) Simulate stochastic road profile variations. The idealization of road profiles included the superposition of two stochastic variations: i) the road surface variation (micro-scale continuous, including smooth variations and random bumps or holes), and ii) the road topography variation (macro-scale continuous variations, including curves and slopes).

2) Simulate the HMMWV suspension parameters using randomly distributed variables to modify the nominal values. Average vehicle speed was varied between 17 MPH and 30 MPH.

3) Perform multibody dynamics simulations of the HMMWV system using as stochastic inputs the road profiles and vehicle suspension dynamic parameters (stiffness, damping). For each simulated road profile, a vehicle multibody dynamics analysis was run to get simulated forces and displacements at each joint of the suspension system.

4) Perform finite element (FE) stress analysis of the selected subsystem. From each HMMWV dynamics simulation a number of local response variables were considerd as random inputs for the stochastic FE stress analysis of the Front-Left Suspension System (FLSS). An efficient, specialized high-performance computing (HPC) stochastic finite-element analysis (SFEA) code was employed.

5) Compute the local stresses refined using stochastic response surface approximation (SRSA) models. These SRSA models were based on high-order stochastic field models that are capable of handling non-Gaussian variations, and non-linear correlations between component variables.

6) Perform durability analysis under random corrosion-fatigue damage using stochastic progressive cracking models based on cumulative damage mechanics nucleation models and fracture mechanics crack propagation models. For reliability prediction at each FLSS critical location, probabilistic distribution models (based on the Lognormal and/or Weibull distributions) were applied.

7) Incorporate uncertainty effects due to the limited-size of the FEA simulation dataset.

8) Incorporate stochastic prediction model updating to integrate the computational predictions with the evidence from the test data (for stresses) and field data (field failures).

The technical details are more complete provided in the paper from the 2010 U.S. Army GVSETS symposium, which is reference in the bibliography. We will only summarize important points here.

2. OPERATIONAL ENVIRONMENT

The idealization of road profiles includes the superposition of two stochastic variations: i) the road surface variation (micro-scale continuous, including smooth variations and random bumps or holes), and ii) the road topography variation (macro-scale continuous variations, including curves and slopes).

Stochastic simulations of the operating environment were obtained by changing 1) road surface profiles 2) random topography and 3) vehicle average operating speed. Road profiles were either 5000 feet or 1500 feet in length, with both high and low correlation variations in the transverse direction. Topology on the road included rolling hills with short chicanes, long winding curves or no topology at all (straight road). The average vehicle speed was either 17 MPH or 30 MPH.

3. HMMWV BEHAVIOR SIMULATION

In this project the values of the total vehicle inertia for the HMMWV were selected based on model number M966 (TOW Missle Carrier, Basic Armor without weapons), since they were available. Tires used for all simulations were the bias-type 36x12.5. Front tire pressures of 20

pounds per square inch (psi) and rear tire pressures of 30 psi were maintained on the HMMWV [1]. In light of the importance of the tire/road interaction due to the stochastic modeling of the road profiles, a co-simulation environment was used to accurately capture the vehicle dynamics. A specialized code was used to simulate the multi-body dynamics of the HMMWV vehicle, including the tire-road interaction. Tire-road interaction is the single greatest source of force loading on a ground vehicle, and special care must be taken with that modeling.

The modeling methodology divides a vehicle in subsystems that are modeled independently. Parameters are applied to the topology of a subsystem and a set of subsystems are invoked and integrated together at simulation time to represent the vehicle model. The subsystems present in our model include: a chassis, front and rear suspension, anti-roll bar, steering, brakes, a powertrain and four wheels. All the major subsystems (front/rear suspension, steering, roll bar and powertrain) are connected to the chassis with bushing elements. Driver controls were created in the event builder as a sequence of maneuvers.

4. SUSPENSION SYSTEM STRESS ANALYSIS

Figure 1 shows the FLSS model used for the HMMWV vehicle multi-body dynamics analysis and the stochastic FEA. The stochastic FEA code is a result of integrating a typical finite element code with advanced high-performance computing (HPC) numerical libraries developed in national labs and top universities [1]. To be highly efficient for large-size FEA models, the stochastic FEA code incorporates both global and local, sequential preconditioners. The expected speed up coming from stochastic preconditioning is at least 4-5 times for linear FEA problems and about 10-15 times for highly nonlinear FEA problems. The comparative FEA parallel run time results shown in Table 1 show a near ideal speed-up when increasing the number of processors from 6 to 24, if the computational size of the problem is large enough to overcome the communication overhead of the parallel FEA.

We also considered that the HMMWV model suspension parameter variations are stochastic. For each wheel suspension system there are 13 random variables [1]. A number of 36 vehicle dynamics joint variables were used as random inputs for stochastic FE stress analysis of FLSS. Each joint force component was used to scale the local stress influence coefficients computed for unit forces in the joints.

To compute local stresses in subsystem components, we used traditional refined stochastic response surface approximation (SRSA) models that are based on high-order stochastic field models that are capable of handling highly nonlinear non-Gaussian variations. Two SRSA models were applied: i) 3-Level Hierarchical Model (3LHM) and ii) Meshless Fast Probability Integration Model (MPFI)[1]

5. PROGRESSIVE DAMAGE MODELS

For fatigue damage modeling, several models were used, including crack initiation models and crack propagation.

Both the constitutive stress-strain equation and strain-life curve are considered to be uncertain curves. The four strain-life curve (SLC) parameters are modeled as random variables with selected probability distributions, means and covariance deviations. We also included correlations between different parameters of SLC. This correlation can significantly affect the predicted fatigue life estimates as shown in our GVSETS paper [1]. Both the stress intensity threshold and material toughness are considered as random variables. Anywhere we could incorporate uncertainty, we did so.

To include the corrosion-fatigue effects, corrosion pit growth models were used. The total corrosion-fatigue damage in the crack nucleation stage is computed using a generalized interaction curve between corrosion and fatigue damages, while the in crack propagation stage is computed by linear fracture mechanic models (Forman model) for which the stress intensity factors are adjusted based on local crack size including both the fracture crack and the pit depth [1]. As before, uncertainty was incorporated.

6. PROBABILISTIC LIFE AND RELIABILITY PREDICTION

For probablistic life and reliability prediction we considered probabilistic life models based on Lognormal and Weibull probability distributions. We also considered the effect of maintenance activities on predicted reliability including uncertainties related to the maintenance schedule, crack detection and sizing and the crack damage repair efficiency. We considered the uncertainties in the maintenance activities that are related to the prediction accuracy of non-destructive inspection (NDI) techniques and component repairs.

7. BAYESIAN AND BAYESIAN-PROBABILITY TRANSFORMATION UPDATING

In addition to the classical Bayesian updating, we also implemented a novel stochastic model updating that

couples the Bayesian updating (briefly BU) with a probability transformation (briefly PT) algorithm. The novel stochastic model updating procedure is called Bayesian-Probability Transformation updating, or briefly the BPT updating. The probablity transformation aspect incorporates the stochastic bias function between the statistical predicted data and the experimental data. The novel stochastic model updating combines the "soft" evidence via Bayesian updating with the "hard" evidence via probability transformation. The improvement is exceptional as it is shown in the case studies section.

8. MODELING UNCERTAINTIES

A two-level nested simulation loop was implemented for including the effects of a limited number of statistical FEA simulations on predicted risks. It should be noted that the two-nested simulation loop approach requires a number of computational FE analysis runs that is equal to the product of the simulation numbers of the inner loop (stochasticity effects) and outer loop (modeling uncertainty effects).

9. SENSITIVITY STUDY RESULTS

A signficant number of sensitivity studies were performed for the HMMWV FLSS reliability. These sensitivity studies are shown elsewhere [1]. Herein, due to the very limited size of this paper we include only few sensitivity studies that address some aspects of important novelty.

9.1 Effect of Statistical Correlation of Strain-Life Parameters

Predicted life is sensitive to slight changes in the nonlinear statistical correlation between the strain-life model random parameters. Please note that the marginal probability distributions of the strain-life model parameters are maintained the same. Changes are only in the correlation structure between these random parameters. There are four stochastic parameters, σ_f , ε_f , b and c that are included in the probabilistic strain-life equation [1]. To include the nonlinear correlation between different stochastic input parameters, we used a generalized marginal probability transformation (GMPT) approach to represent the non-Gaussian joint probability density of those variables by their Gaussian images (also called translational fields) applied in conjunction with statistical clustering for computing mixture-based joint PDFs. Figure 3 shows the effect on nonlinear correlation between the 4 parameters of the strain-life curve for two case studies. More details are in reference [1]. Figure 3 compares the simulated strain-life curve obtained for the statistical Database A (higher correlation) and Database B (lower correlation). It should be noted that the resulting scatter of the two simulated strain-life curve is very different. As an example, if we consider the lowest strain-life curve sample for a given strain range of 2.0E-3, then, the computed fatigue cycle life is only 100 cycles for Database B, but 50,000 cycles for Database A. This drastic change in the computed fatigue life is a solely result of changing the correlation patterns between the strain-life curve parameters. It should be noted that the marginal statistical moments and PDFs were preserved. The correlation pattern change was this only change that was made between Database A and Database B (the marginal PDFs are not modified at all). It is obvious that the above example shows how important is for an accurate life prediction to capture correctly the complex statistical dependences, i.e. nonlinear statistical correlation patterns, between the strain-life curve parameters. Same remarks could be extended to crack propagation models such as Paris Law or Forman linear-fracture mechanics-based models. *This is an extremely important probabilistic modeling aspect that is most often ignored in practical applications.*

9.1 Effect of Limited Simulation Data

A study was done on the effect of modeling uncertainty on the FLSS predicted life due to the limited number of FEA simulations, only 250 samples, for different selected reliability levels, including mean, 99% and 95% exceedance probabilities. It should be noted that the 99% reliability life is about half of the 95% reliability life. Also the 99% reliability life is about 15-20 times shorter than the mean life. The effect of modeling uncertainty for the 95% confidence versus the 50% confidence is to reduce the 95% and 99% reliability lives by about 20-30%.

9.2 Pitfalls in Bayesian Updating

Further, we investigated the application of the Bayesian updating for computing the updated bivariate fatigue stress probability distribution based on available experimental data. The bivariate fatigue stress distribution includes both the quasi-static stress component (in X direction in the plots) and the vibratory stress component (in Y direction in the plots). We considered 5 random test data. The original and updated PDF of the bivariate stress using Bayesian updating (BU) is shown in the Figure 2 left plot. It should be noted that the updated PDF departs from original PDF even though the prediction accuracy is perfect. Our new method, BPT, however provides an updated PDF that overlaps with original PDF since prediction accuracy is perfect. The above results show a very serious pitfall of the classical Bayesian updating that is currently extremely popular and widely applied by engineers as a black box. Please see the longer paper [1] for more details of this alarming result.

9.3 Effects of Maintenance Operations

Finally, we discuss the effects of maintenance uncertainties on the FLSS reliability. First, we investigated

the case of when the target reliability level or POF is given and the schedule of maintenance events needs to be determined. Results are presented in Table 1. Three cases were considered for the POF equals to 1.0E-05, 1.0E-04 and 1.0E-03. Using the developed integrated reliability framework, we determined the required maintenance schedule, the number of scheduled maintence events (SME), the maintenance intervals, the cumulative number of repairs, the instantaneous failure probabilities (POF) and the mean hazard failure rates (MHFR) per maintenance intervals.

It should be noted that for the 1.0 E-05 target POF, the numbers of scheduled maintenance events and the number of repairs are both about twice than the number of maintenace events and the number of repairs needed for the 1.0 E-03 target POF. This indicates a scheduled maintenance cost of 4 times higher for the 1.0 E-05 POF than the 1.0 E-03 POF. However, the real risks are shown by the MHFR results not instantaneus POF. The MHFR shows a risk ratio over time that is about 50 times larger for the 1.0 E-03 target POF case. It should be noted that the highest maintenance-related cost is the unscheduled maintenance event (UME) cost associated with the vehicle failure during field operations. This UME cost is about 20-100 times larger than the SME costs. Thus, if we assumed that the UME cost is 20 times the SME costs, the use of the 1.0 E-03 target POF will produce a UME cost of 50 x 20 = 1,000 times larger than the use of 1.0 E-05 target POF. Thus, overall the maintenance cost will be much larger for the 1.0 E-03 target POF.

We also studied the effects of the maintenance interval, inspection technique, inspection operator skills and crack size rejection limit criterion on the FLSS reliability as shown in Table 2. The largest impact on reliability is produced by the maintenance scheduling and the inspection operator skills. An unskilled operator could increase the fatigue failure risks by tens of times comparing with a highly skilled operator. Training and environment control are key factors to ensure skilled operators. The effect of the selected inspection technique on the FLSS reliability is also important. We considered Eddy Current inspection versus Visual inspection for cracking detection. All maintenace intervals are 185 days, each day including 24 hour driving on moderate roughness roads. Results show that the Eddy Current inspection is 6-7 times safer than Visual inspection at twice cost (based on the cumulative number of repairs).

10. CONCLUSIONS

An integrated HPC reliability framework has been developed to address the many challenges of the ground vehicle reliability prediction problem. We have accommodated many of them.

Specific conclusions are:

1) Our framework can accurately handle both aleatory and epistemetric uncertainty, allowing for more confidence in the prediction of the reliability of the ground vehicle.
2) We have learned more about what factors have large impact on the reliability assessment and have developed strategies to deal with those factors.
3) We have shown that incorporating “hard” and “soft” data by combining Bayesian updating with the test-predicted bias probability transformation is a significant advance over traditional Bayesian updating.
4) We have extended the engineering design process to consider maintenance as a source of both engineering design parameters and also uncertainty in the process. The resulting reliability assessment can predict the result of changes in maintenance intervals, or the sensitivity to disruptions and variability in this area.
5) The road surface variations are highly non-Gaussian, being rightly-skewed toward larger amplitudes. The non-Gaussian variation aspects of the road profiles have a significant impact on the predicted vehicle fatigue reliability. This is a very important modeling aspect that was ignored in practice over a long period of time.
6) The effect of the limited number of FEA simulations (herein 250 samples) impacts significantly on reliability prediction.

The framework is reaching maturity, and should soon be ready to use on new ground vehicle systems, improving the reliability of the U.S Army’s fleet in many ways. The potential impacts of this work are significant, and the U.S. Army of 2020 should be better as a result of this research. While more work needs to be done, the case study on the HMMWV FLSS was comprehensive enough to show that real results can already be obtained, and the Army can see immediate benefits of using this framework.

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Table 1. Required Maintenance for FLSS for Different Target Failure Probability (POF) Levels for Moderate Roughness Roads (No Additional Armour Weight Included)

Target Probability of Failure (POF)	Computed Probability of Failure (POF)	Number of Scheduled Maintenance Events	Mean Maintenance Interval (days)	Cumulative Number of Repairs per Component	Mean Hazard Failure Rate For Entire Period (per day)
1.0 E-05	1.1 E-05	23	155 (372) (1.02 years)	18	7.5 E-08
1.0 E-04	1.1 E-04	17	205 (492) (1.35 years)	15	5.3 E-07
1.0 E-03	1.0 E-03	12	285 (684) (1.87 years)	11	3.5 E-06

Table 2. Maintenance Analysis Sensitivity Studies for FLSS Reliability for Moderate Roughness Roads (No Additional Armour Weight Included)

Sensitive Study Parameters	Average Maximum POF Per Interval	Average Hazard failure Rate	Number of Repairs Per 100 Parts
Maint. Interval=155 days	1.29003e-5	8.32275e-8	853
Maint. Interval=185 days	5.39682e-5	2.91720e-7	745
Maint. Interval=230 days	2.56768e-4	1.11638e-6	617
Visual Inspection *	3.4119e-4	1.84428e-6	382
Eddy Inspection *	5.39682e-5	2.91720e-7	745
Worst Skill Operator *	2.37889e-3	1.28589e-5	280
Best Skill Operator *	3.38781e-5	1.83125e-7	384
Rejection crack size = 0.0 in*	5.39682e-5	2.91720e-7	745
Rejection crack size = 0.15 in*	1.79505e-4	9.70295e-7	170

NOTE: * Constant maintenance intervals of 185 days were considered.

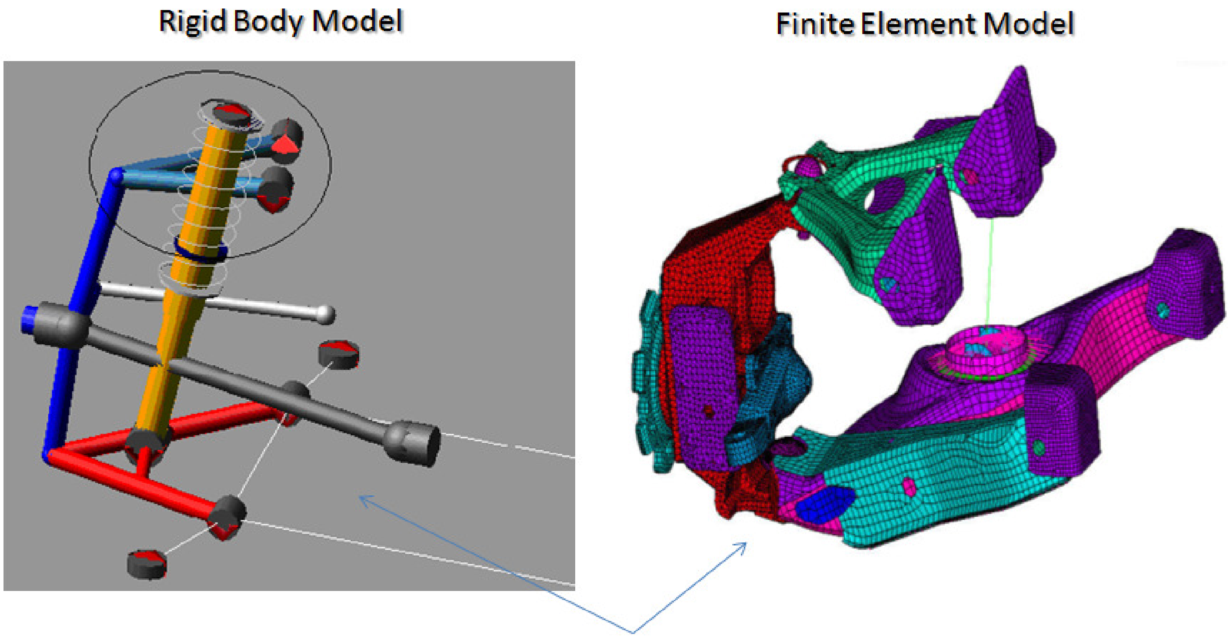


Figure 1: Front-Left Suspension System (FLSS); Vehicle model (left), and FEA model (right)

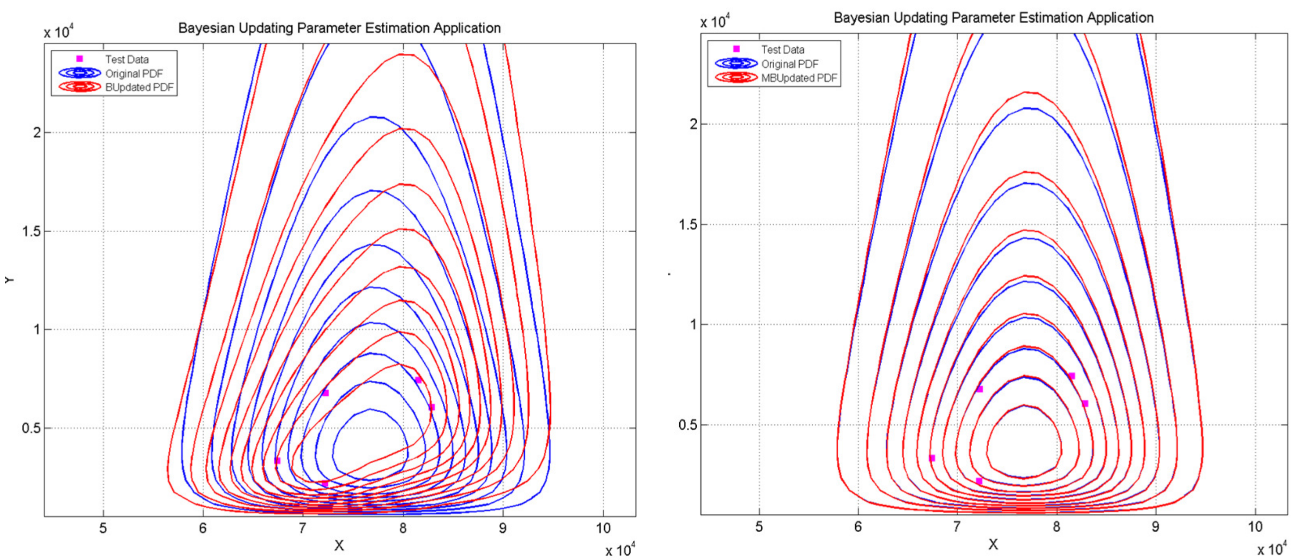
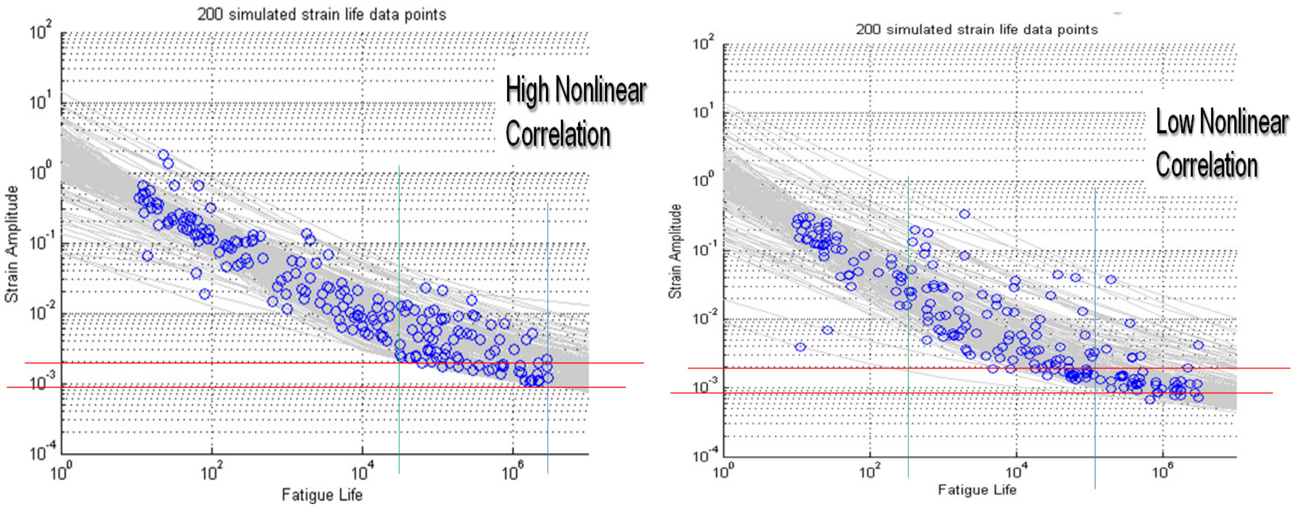


Figure 2 Prior & Posterior PDF Using BU (left) versus BPT (right) for 5 Tests With No Prediction Error



Database A Database B

Figure 3 Simulated Strain-Life Curve Including Nonlinear Correlation Between Parameters